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Valuing Access to Water –

A Spatial Hedonic Approach Applied to Indian Cities

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Abstract

An important infrastructure policy issue for rapidly growing cities in developing countries is how to raise fiscal revenues to finance basic services in a fair and efficient manner. This paper applies hedonic analysis that explicitly accounts for spatial spillovers to derive the value of improved access to water in the Indian cities of Bhopal and Bangalore. The findings suggest that by looking at individual or private benefits only, the analysis may underestimate the overall social welfare from investing in service supply especially among the poorest residents. The paper further demonstrates how policy simulations based on these estimates help prioritize spatial targeting of interventions according to efficiency and equity criteria.

This paper—a product of the Sustainable Rural and Urban Development Team, Development Research Group—is part of a larger effort in the department to understand the contribution of urban public services to household welfare and overall quality of life. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at udeichmann@worldbank.org.

Valuing Access to Water –
A Spatial Hedonic Approach Applied to Indian Cities*

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I. Introduction

The population of Indian cities is currently growing at a rate of 3 to 4 percent per year, in line with the urban growth rates of cities in developing countries as a whole. This implies that their population will double within the next 17 to 23 years. Even if growth rates continue to decrease from their highs of more than 5 percent in the 1960s and 1970s, this means that local policy makers need to deal with a significant increase in the demand for public services while, at the same time, addressing the backlog of investments in under-serviced areas.

Municipal managers face these challenges in an environment in which they have been given significant new responsibilities. As in many other developing countries, urban policy in India had historically been formulated centrally by the national government with relatively little concern for local needs and interests. City officials simply implemented policies using funds allocated by state and national government. This changed with the passing of the 74th Amendment of the Indian Constitution in 1993. Since then, more and more administrative and fiscal authority has been devolved to local governments. Greater local control should lead to more appropriate local policy making. But it will also require cities to become financially more independent by expanding local revenue generation.

Cities are therefore exploring options to generate funds locally, either through user charges and fees or through property taxes (Lall and Deichmann 2006a). Successful introduction of such revenue schemes in an environment where residents are used to heavily subsidized or free service access depends on demonstrating that the charges realistically represent the benefits obtained by households in return. At the same time, policy makers need reliable estimates of potential revenue generation to relate benefits to the actual costs of service provision which in turn influence financing strategies. Furthermore, equity concerns guide many policy decisions. Urban managers require tools that enable prioritization of investments according to chosen equity-efficiency considerations, for instance, by targeting the poorest areas first or those areas where returns are highest.

This paper contributes to this debate by proposing an improved strategy for estimating benefits from infrastructure investments in urban neighborhoods. We assume that public services are capitalized in the value of a dwelling unit. Hedonic analysis of house prices or rents conditional on service access will therefore yield estimates of the contribution of individual housing unit characteristics and thus the willingness-to-pay (WTP) of residents for those characteristics. In contrast to the standard hedonics and WTP literature, we use a spatial framework that allows us to measure both direct effects and externality spillovers from upgrading by neighbors. We illustrate this approach in a valuation of water services in two Indian cities, Bangalore and Bhopal, and compare the results with those obtained from a standard WTP questionnaire. The results suggest that standard hedonic analysis considerably underestimates the benefits from service upgrading. The higher spatial econometric estimates are surprisingly consistent with households' expressed WTP. Finally, we present a policy analysis based on simulation of different upgrade scenarios that is based on predicted values for individual observations in our household survey rather than on marginal willingness-to-pay.

The remainder of the paper is structured as follows. The next section discusses the use of hedonic models for valuation purposes. Section III describes the estimation strategy. The data used in this analysis and estimation results are described in Sections IV and V. We derive the marginal willingness to pay for improved water availability in Section VI and present a policy analysis using a simulation exercise in Section VII. Section VIII concludes.

II. Hedonic Analysis of Housing Characteristics and Public Services

Valuation of public services and other housing attributes has been addressed through methods such as contingent valuation (Whittington 2002), conjoint and discrete choice analysis (Earnhart 2002) and hedonic specifications (Malpezzi 2002). In hedonic models, dwelling unit prices represent the sum of expenditures on a bundle of characteristics that can be priced separately. If $z=(z_1,\ldots,z_n)$ is a set of characteristics of the home, the price of the home is determined by some hedonic function, $p(z)$, according to prevailing market clearing conditions. The set of characteristics that determine home values consists of structural attributes of the home itself, such as the floor area, lot size, and construction material, as well as the availability of public services such as clean water supply or electricity. Such models have been used in developing countries to determine the optimum housing characteristics for low income groups (Follain and Jimenez, 1985) and for valuation of access to specific services (North and Griffin, 1993; Crane et al., 1997; Oliveira and De Morais, 2000, and Knight et al. 2004 among others).

Estimating the hedonic price function using a set of observed housing values and dwelling unit characteristics yields a set of implicit prices for housing characteristics that are essentially willingness-to-pay estimates. These can then be used in a second stage analysis, where the WTP estimates are used as the dependent variable in an inverse demand function. Estimates of income elasticities of demand can then be derived for various parts of a city or subgroups of the population. This allows analysis of various upgrading scenarios, for instance, in low-income neighborhoods.

Recent empirical econometric work has addressed the potential bias and loss of efficiency that can result when spatial effects are ignored in the estimation of hedonic models (e.g., Pace and LeSage 2004). Spatial patterns in the housing markets arise from a combination of spatial heterogeneity and spatial dependence (Anselin, 1998). Spatial heterogeneity—essentially the existence of discrete submarkets—can originate from characteristics of the demand, supply factors, institutional barriers or racial discrimination that cause house price differentials across neighborhoods. Spatial autocorrelation or spatial dependence, on the other hand, means that prices or characteristics of houses that are nearby are more similar than those of houses that are farther apart—that is, housing prices vary more continuously due, for instance, to spatial spillovers. In practice, spatial autocorrelation may be observationally equivalent to spatial heterogeneity and (Anselin, 2001) or it may result from spatial heterogeneity that is not correctly modeled (Baumont, 2004).

Besides being the result of some substantive underlying process such as spatial spillover or some form of contagion, spatial dependence may also arise from measurement problems in explanatory variables, omitted variables, and other forms of model misspecification. The presence of spatial autocorrelation has significant bearing on parameter estimation. If it is ignored, OLS may lead to inconsistent estimates and incorrect statistical test results. If the residuals are spatially correlated, OLS estimation would underestimate the residual variance and the t-statistics would be upwards biased. This may lead to erroneously concluding significance of some parameters. Some examples of the use of spatial hedonic models in the context of valuation of environmental amenities are Kim et al. 2003, Beron et al. 2004, Brasington and Hite 2005, Anselin and Le Gallo 2006, and Anselin and Lozano-Gracia 2007a. The present paper extends spatial hedonic approaches to the analysis of service access in developing country cities.

III. Estimation Strategy

We estimate a log-linear hedonic function for house rents in Bhopal and Bangalore and take an explicit spatial econometric approach by testing for spatial autocorrelation and controlling for its presence in the final specification estimated. The spatial econometric literature (see Anselin 1988) differentiates between two types of spatial dependence that result in two main spatial models: the spatial lag and spatial error models. The spatial lag model accounts for spatial dependence by introducing a spatially lagged dependent variable into the model, while the spatial error specification includes a spatially correlated error term.

Following Anselin (1988), we carry out a so-called forward specification analysis (see also Florax et al. 2003), and first obtain ordinary least squares (OLS) estimates for the hedonic model. Next, we test the residuals for the presence of spatial autocorrelation using Lagrange Multiplier test statistics for error and lag dependence, as well as their robust forms, and proceed with the alternative spatial regression model thus selected (Anselin et al. 1996). The estimation results consistently show very strong evidence of positive residual spatial autocorrelation favoring the spatial lag alternative (see Appendix 1, Tables AA1 and AA2).

In a hedonic model, a spatial lag model can be specified as follows:

$$p = \rho Wp + X\beta + u$$

where p is an $n \times 1$ vector of observations on the dependent variable, X is an $n \times k$ matrix of explanatory variables, u is an $n \times 1$ vector of i.i.d. error terms, β is a $k \times 1$ vector of regression coefficients, ρ is the spatial autoregressive parameter, and W is a $n \times n$ spatial weights matrix. A spatial weights matrix incorporates the neighborhood relations between observations and is a standard tool employed in spatial econometric analysis (see Anselin 2006 for extensive discussion).[5] It should be noted that since the house locations constitute a sample, the

[5] For this application we used a queen contiguity criterion to define neighbors. This is obtained by first taking the point coordinates of the house locations and creating a Thiessen polygon tessellation centered on each house. Polygons with common sides and vertices designate house locations as queen neighbors. On average, the weights matrix contains 7 neighbors for each location. In addition, we also used two weights

neighborhood relations in the spatial weights are only proxies for the true neighbors. The underlying assumption is that the spatial variation among sampled "neighbors" is representative of that among the true neighbors, an assumption commonly taken in spatial hedonic models. We are comfortable that the sample design employed in these surveys supports the conclusions we draw from this analysis. However, ideally it would be desirable to employ sampling designs that consider neighborhood structure explicitly, for instance by sampling households randomly and then including a number of direct neighbors for each households. Very few surveys have employed such as design, the US American Housing Survey being an exception (Ioannides 2002).

IV. Data and Variables

Detailed household data for developing country cities are scarce. Most such data are collected at the national level through Living Standards Measurement Surveys or Demographic and Health Surveys. These tend to distinguish urban and rural areas, but the number of observations in each urban area is too small for city-specific analysis. In this paper we use comprehensive and geographically referenced information from urban household surveys for 2905 households in Bangalore and 2508 households in Bhopal (for further details on this data see Deichmann et al. 2003, Lall et al. 2004, Lall and Deichmann 2006b). These surveys were conducted in 2001 and 2003 respectively. The available variables differ slightly across the two cities since the original surveys were not totally identical. The key indicator in hedonic housing market analysis is the price or rent of the dwelling unit. Due to high official transaction costs, most recorded sales in Indian real estate markets do not reflect actual transaction amounts. Rents are also often artificially low due to rent control and therefore do not always match actual market rents. The surveys therefore asked households to report what they believe would be the market rent for a similar house in their neighborhood. Therefore this variable represents an estimated value reported by the surveyed individual. The survey team compared these values selectively to transactions revealed by real estate agents in the survey cities. This confirmed that, overall, residents have a fairly good idea of market rents. In our regression analyses, we apply a log

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matrices based on a nearest neighbor relation among the locations, for respectively 7 and 14 neighbors. The three weights matrices are used in row-standardized form. Although the remaining analysis refers only to the results using a queen weights matrix, the results are consistent for the alternative weights matrices based on a nearest neighbor relation.

transformation to correct for the high degree of skewness. House characteristics such as size, number of rooms, number of bathrooms, material of walls, roof, and floor, and alternative sources of water and electricity are also contained in the survey. Table 1 describes the variables included in the hedonic regressions and indicates when they are not available for both cities.

Table 1: Description of Variables Used in Hedonic Models

	Dependent Variable
Lnrent	Log of estimated house rent
	House Characteristics
Size	Size of house plot in sq. ft.
Number of Rooms	Number of rooms
Number of Bathrooms	Number of bathrooms
Floors	Indicator variable for floors of stone of better material
Walls	Indicator variable for walls of brick of better material
Roof	Indicator variable for Roof of Brick of better material
Kitchen	Kitchen inside the house
Electricity	Indicator for access to metered electricity
Toilet-Sewer	Indicator for toilet connected to sewer system
	Neighborhood Characteristics
Women safe [a]	One if neighborhood feels safe for women, zero otherwise
Crime decr. [b]	One for crime decrease in last five years
Open Dump [a]	No open dump near house
	Access to Water
Water - DPW	Days per week water is available through direct connection
	Other sources of Water: Indicator Variables
Else's	Someone else's connection
Hand Pump	Individual Hand Pump Well
Tube Well	Individual Tube Well
Fountain	Public Fountain
Community Tube	Community Tube Well
Community Tap	Community Tap
Community Hand Pump	Community well/hand pump
Tanker	Tanker
Other	Other vendor
Rain	Rainwater harvesting
Surface	Surface water
	Ward Dummies
Ward	Indicator variable for every ward

Notes: (a) Bhopal only; (b) Bangalore only.

Table 2 Bangalore: Descriptive Statistics

Variable Name	*Mean*	*Std. Dev*	*Min.*	*Max.*
House Rent	3085.398	3254.841	99	45000
Size	1100.871	873.5702	100	18000
Number of Rooms	4.554208	2.75	1	25
Number of Bathrooms	1.2565	0.7743	0	25
Floors	.98787	0.1094	0	1
Walls	0.9629	0.1863	0	1
Roof	0.8144	0.3888	0	1
Kitchen	0.9941	0.0764	0	1
Electricity	0.9889	0.1044	0	1
Toilet-Sewer	0.3605	0.4802	0	1
Crime decr.	0.2179	0.4129	0	1
Water - DPW	3.3399	2.1079	0	7
Hand Pump	0.0077	0.0875	0	1
Tube Well	0.1345	0.3412	0	1
Fountain	0.1907	0.3929	0	1
Community Tube	0.0606	0.2387	0	1
Tanker	0.0040	0.0634	0	1
Other	0.0102	0.1009	0	1
Surface	0.0025	0.0506	0	1

Table 3 Bhopal: Descriptive Statistics

Variable Name	*Mean*	*Std. Dev*	*Min.*	*Max.*
House Rent	1704.315	2706.4	50	50000
Size	760.2766	772.0118	70	8000
Number of Rooms	3.5526	2.7912	1	35
Number of Bathrooms	1.1343	0.5522	0	5
Floors	0.8703	0.3360	0	1
Walls	0.8114	0.3912	0	1
Roof	0.5354	0.4988	0	1
Kitchen	0.9901	0.0990	0	1
Electricity	0.7505	0.4328	0	1
Toilet-Sewer	0.1750	0.3800	0	1
Women safe	0.8713	0.3348	0	1
Open Dump	0.4859	0.4999	0	1
Water - DPW	3.1593	3.4391	0	7
Else’s	0.0375	0.1900	0	1
Hand Pump	0.0151	0.1219	0	1
Tube Well	0.0666	0.2495	0	1
Community Tube	0.0552	0.2284	0	1
Community Tap	0.3234	0.4679	0	1
Community Hand Pump	0.1093	0.3121	0	1
Tanker	0.0270	0.1623	0	1
Other	0.0010	0.0322	0	1
Rain	0.0005	0.0228	0	1
Surface	0.0020	0.0456	0	1

V. Regression Results

In both cities, we use the log of house rent as the dependent variable. For the main policy variable of interest, water availability, we use the number of days per week water is available in the house through a direct connection. The estimation results show the expected patterns in terms of signs and significance. For Bhopal, positive and very significant coefficients are observed for Size, Baths, Rooms, Floor, Walls, Roof, and Electricity (see Table AA1). Water availability measured through DPW is positive and significant. Among additional water sources different from an individual water connection, only the presence of a tube well has a negative and significant effect while the coefficient for Rain is positive and significant. Indicator variables are included for every Ward to account for neighborhood characteristics for which data are not available. Some of these variables remain significant even after introducing the spatial lag into the model. The coefficient estimated for the spatial lag is above 0.24 and very significant in all cases. The LM statistic for remaining spatial autocorrelation in the LAG model suggests the presence of remaining spatial autocorrelation of unspecified form. Therefore, following the approach suggested in Anselin and Lozano-Gracia (2007a), it is appropriate to use the Kelejian-Prucha Heteroskedasiticity and Autocorrelation Consistent estimator (HAC) (Kelejian and Prucha 2007). We employ three alternative kernels (epanechnikov, bisquare, and triangular) to further assess the robustness of our findings. We also compare the results to estimated standard errors that only correct for unspecified heteroskedasticity (White 1980). For the standard errors and confidence intervals using two standard deviations shown in Table AA1 we find that the largest changes in standard errors are seen when we go from classical to the White correction, with a much smaller effect for the spatial adjustment.

Estimates for Bangalore are shown in Table AA2. We observe a positive and very significant coefficient estimate for water availability measured through DPW. House characteristics have positive and significant effects as expected; the coefficient of number of bathrooms, however, loses its significance when going from the Classical to the HAC standard errors. The bathroom variable is significant at the 1% level when looking at the classical standard errors but only significant at 5% when moving to the more appropriate HAC standard errors. Other sources of water availability that show negative and significant results are fountain and community tube well. The coefficient for the spatial lag is also above 0.24 and very significant as is the case for Bhopal. The LM statistic for the lag model confirms the presence of remaining spatial autocorrelation and heteroskedasticity suggesting the need to use the HAC estimator. The more realistic measure of standard errors provided by the HAC estimator is particularly important in assessing the precision of the derived welfare measures discussed in the following section.

VI. Marginal Willingness to Pay for Changes in Water Availability

In this section we look at the valuation of water accessibility computed from the parameter estimates discussed in the previous sections. In a hedonic framework the MWTP is defined as the derivative of the hedonic price equilibrium equation with respect to the characteristic of interest, in this case access to water. In a non-spatial log-linear model, the MWTP equals the estimated coefficient for the water variable (DPW) times the price (P), [6] or

$$MWTP_g = \frac{\partial p}{\partial g} = \hat{\beta} p, \tag{1}$$

where g is DPW.

For the spatial lag model, the total effect consists of the direct effect and a spatial multiplier which is due to the fact that benefits from a household's improved water access spill over to neighbors which, in turn, benefit the household.[7] This spatial multiplier effect needs to be accounted for to accurately compute the MWTP, as shown in Kim et al. (2003). For a uniform change across all observations, the multiplier effect is:

$$MWTP_g = \frac{\partial p}{\partial g} = \hat{\beta} p \left(\frac{1}{1 - \hat{\rho}} \right), \tag{2}$$

with $\hat{\rho}$, as the estimate of the spatial autoregressive coefficient. Small and Steimetz (2006) stress the need to separately estimate the direct effect in (1) and the multiplier effect included in (2). In their view, the multiplier effect should only be considered as part of the welfare calculation in the case of a technological externality associated with a change in amenities. In the case of a purely pecuniary externality, the direct effect is the only correct measure of welfare change.

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[6] We use the mean house rent in the sample to calculate the MWTP

[7] In other words, each location is its neighbor's neighbor, similar to the reflection problem in Manski (1993). This is a main difference to dependence in time series models which is uni-directional.

A strong argument in favor of using a spatial lag specification (where warranted by the data) is that it allows the two effects to be considered explicitly which clarifies the tradeoffs between spatial and non-spatial effects in a policy context. In Tables 4 and 5 we report the calculated MWTP for changes in DPW of water availability for the cities of Bangalore and Bhopal respectively. For the lag models, we include both the direct effect as well as the total effect. In addition to point estimates, we list a confidence band of +/ − two standard errors around the point estimate. In the non-spatial models and for the direct effect computation, the standard errors are those reported for the regression coefficients. In the spatial multiplier estimation, the standard error of $\hat{\beta}$ and $\hat{\rho}$ need to be accounted for jointly, which we implement by means of the delta method (see, e.g., Greene 2003, for further computational details).

We report the results for a queen spatial weights matrix and with standard errors based on the classic form, the White and the HAC formulation using an epanechnikov kernel[8]. MWTP are estimated for a change of one day per week. For both cities we see some difference between the OLS estimate and the result from the LAG model, with, in general, the LAG estimate being larger. For Bhopal, the OLS estimate would suggest a point estimate of INR 44 (Table 4). The LAG estimate on the other hand, gives an estimated MWTP of INR 54. For the case of Bangalore, MWTP values are reported in Table 5. The OLS estimated MWTP is INR 101 while the LAG model gives an estimate of INR 117. On average, households have access to water around 3 days per week in both cities. However, the distribution of water availability is quite different for Bhopal and Bangalore. While for Bhopal more than 80% of the households are concentrated on the tails of the distribution of water access, having either zero or seven days of water availability, in Bangalore 50% of the households have water available for 4 days in a week. From Tables 4 and 5 we see that for a similar change in water availability, on average, households in Bangalore are willing to pay almost twice as much as households in Bhopal. This is not surprising given that house rents are almost twice as much in Bangalore compared to Bhopal.

[8] Results were consistent when using bisquare and triangle kernels.

Table 4 Bhopal: Estimated MWTP and confidence intervals (INR)

		BHOPAL	
	OLS	*LAG- Direct*	*LAG – With Multiplier*
MWTP – water (dpw)	44	41	54
Confidence Intervals			
Classic	13 - 69	14 - 69	19 - 90
White	13 - 70	14 - 70	19 - 90
HAC -epanechnikov	11 - 72	12 - 71	16 - 93

Table 5 Bangalore: Estimated MWTP and confidence intervals (INR)

		BANGALORE	
	OLS	*LAG- Direct*	*LAG – With Multiplier*
MWTP – water (dpw)	101	89	117
Confidence Intervals			
Classic	48- 153	37 - 140	49 – 185
White	46 - 155	35 - 142	46 - 188
HAC -epanechnikov	41 - 160	33 - 144	43 - 191

Since local public service provision was one of the main concerns in the two household surveys, the survey instrument also included a standard WTP questionnaire. Households were asked how much they would be willing to pay for improved water access using a stochastic payment card (e.g., Wang and Whittington 2005). Rather than presenting households with only one charge, this design starts with a very high charge which is then gradually reduced. At each step, the household is asked whether they would be willing to pay this charge with answers precoded as *definitely not*, *probably not*, *not sure*, *probably yes*, and *definitely yes*. For Bangalore, the resulting point estimate of WTP for "definitely yes" is INR 119.62, while for Bhopal it is INR 45.14. For "probably yes" they are INR 170.12 and INR 119.34 respectively. This suggests a surprising degree of consistency between our estimated WTP and the survey responses. Although evidence from only two surveys is insufficient to draw general conclusions, the similarity of the two estimates lends credence to the hedonic estimation approach and also suggests that residents are able to quite accurately judge the value of water supply services.

VII. Simulations and Policy Analysis

As an alternative to the traditional analytical derivation of marginal willingness to pay (MWTP) presented in the previous section, we also implement a simulation approach following a methodology similar to the one outlined in Anselin and Le Gallo (2006). The essence of the approach is that valuation is based on the computation of predicted values for individual observations given their actual household characteristics. Average valuation of a given policy change is then obtained by adding the change in the predicted value relative to a benchmark and dividing by the total number of observations. A major advantage of the simulation approach is that it allows greater flexibility, both in the specification of the type of policy experiment (e.g., differential changes in water access) as well as in the valuation. Since the valuation is computed for individual house observations, the results can be obtained for any desired level of spatial aggregation, such as by ward. In essence this boils down to a discrete approximation to the notion of marginal willingness to pay. Given a vector of coefficient estimates $\hat{\beta}$, the conditional expectation $E[p \mid Z]$ is obtained as

$$E[p \mid Z] = \hat{p} = Z\hat{\beta} \tag{3}$$

since $E[\mu \mid Z] = 0$ by assumption.

For the sake of simplicity, assume that interest is focused on attribute Z_k and separate the matrix of observations and corresponding coefficient vector into Z_k and the other variables, as Z = [Z_{-k} z_k] and β = [β_{-k} β_k]. The predicted value can then be decomposed into a part that does not change with the value of z_k and a part that does:

$$\hat{p} = Z_{-k}\beta_{-k} + z_k\beta_k = \hat{p}_{-k} + z_k\beta_k. \tag{4}$$

Consider the prediction $\hat{p}_0$ using the observed values for Z_{-k} and z_k. Now, consider a new vector of attributes z^1_k , reflecting a policy change, such as a given percentage increase in access to water. The new vector of predicted values follows as:

$$\hat{p}_1 = \hat{p}_{-k} + z^1_k\beta_k, \tag{5}$$

with the change in valuation as $\hat{p}_0 - \hat{p}$, or $(z^1_k - z_k)\beta_k$. Since this is a vector of observation-specific changes, it can be averaged over all observations or over any relevant spatial subset of observations.

The presence of a spatially lagged dependent variable in the hedonic equation complicates this approach slightly. Instead of the simple difference, $(z^1_k - z_k)\beta_k$, the total effect is obtained as $(I - \hat{\rho}W)^{-1}(z^1_k - z_k)\beta_k$, where $\hat{\rho}$ is the estimated spatial autoregressive coefficient and $(I - \hat{\rho}W)^{-1}$ is the inverse of a n × n matrix, of the same dimension as the data set. In large samples, a power approximation is used to avoid numerical problems. These procedures are implemented in the PySAL library of routines for spatial analysis (Rey and Anselin 2007). A slight complication pertains to the application of this idea to a log-linear hedonic equation. As is well known, $E[p \mid Z] \neq e^{E[\ln p|Z]}$, but a bias correction needs to be applied to the exponentiated predicted value. As shown in Aitchinson and Brown (1957), the conditional expectation is a function of the variance. In our particular case, the conditional expectation would take the form $E[p \mid Z] = e^{(I-\rho W)^{-1} X\beta + (\sigma^2/2)}$, where σ^2 is approximated using its mean squared error estimate.

Approximate confidence intervals can be computed for the point estimates of the changed valuation in a number of ways. In the current application, we limit our attention to point estimates and use upper and lower bounds for the estimated coefficients to recompute the predicted value. Specifically, this is based on the estimate plus or minus two standard errors. As a starting point, we simulate a uniform change in water availability in the two cities, increasing it by one day for all households. The valuation from this simulation is comparable to the MWTP value obtained from the estimation of the hedonic model.

When considered relative to the mean DPW in each city, one day may constitute a non-marginal change, given that the average availability is around 3 days per week. Therefore, we refine the analysis by focusing on those households that do not attain the mean (DPW < 3). We assess both a uniform as well as a non-uniform change. First, we assess the impact of a 33% change (1 day on average) and a 10% change (around 7 additional hours on average) for those households. More interestingly, we consider non-uniform targeted policy interventions as well. Specifically, we assess a scenario where those same households are "moved up to" 3 DPW of water availability and a scenario where they are guaranteed one day a week of water through a direct connection.

The average valuation from simulating a uniform increase of 33% (one day on average) for the city of Bangalore is INR 196 which is somewhat higher than the MWTP obtained from the lag specification of the hedonic model (INR 117).[9] Similar changes in water availability are simulated for the city of Bhopal. A uniform increase of 33% (one DPW on average) in water access through a direct connection would lead to an average change on house rents of INR 98. For both cities, the total difference in value is divided by the number of observations to obtain the average changes in house rents reported in Table 6. Both Direct and Total (With Multiplier) changes are reported as it was done in the previous section for the MWTP estimates. Table 6

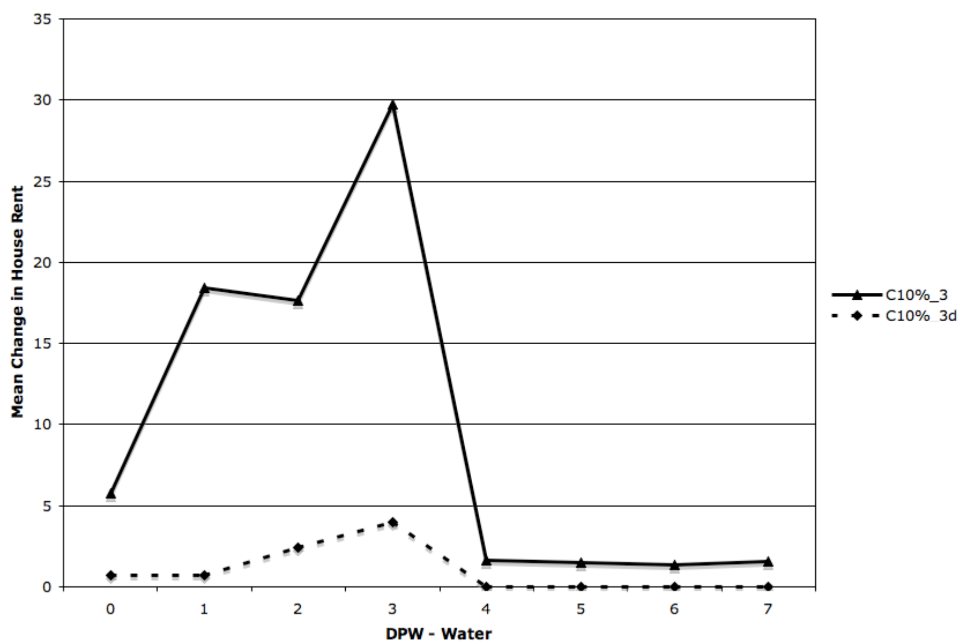
[9] All simulations consider the constraint that access to water must be less than or equal to seven days.

shows the differences in the average changes in house prices if we ignore the multiplier effect. Numbers in parenthesis give the lower and upper bounds for a confidence interval created using two standard deviations from the estimated coefficients.

Table 6: Policy Simulations: Mean Change in House Rents (INR)

Policy Intervention Simulated	*Bangalore*		*Bhopal*	
	Direct	*With Multiplier*	*Direct*	*With Multiplier*
Uniform Increase of 33%	20.98	196.36	13.20	97.64
	(7.13–37.57)	(25.42-1202.7)	(3.04-26.29)	(10.97-504.1)
Increase of 33% for <3 DPW	2.50	22.23	0.76	5.89
	(0.89 – 4.28)	(3.09 –125.75)	(0.2-1.34)	(0.70-27.41)
Increase of 10% for <3 DPW	0.75	6.68	0.23	1.78
	(0.27 – 1.28)	(0.93 – 37.59)	(0.06-0.40)	(0.21-8.25)
Increase to 3 all with <3 DPW	5.28	47.61	6.01	46.40
	(1.92 – 5.28)	(6.72 – 264.5)	(1.54-10.72)	(5.45-219.22)
Increase to 1 all with <1 DPW	1.67	15.12	1.94	15.01
	(0.62 – 2.74)	(2.17 – 82.71)	(0.51-3.40)	(1.79-69.71)

Figure 1: Bangalore: Direct vs. Total (With Multiplier) effects for an increase of 10% in water availability (days per week, DPW) for all households with less than 3 days per week [10]



[10] C10%_3 shows for the total effect while the dotted line labeled C10%_3d shows the direct effect that ignores the multiplier from the spatial model.

Figure 2: Bangalore: Direct vs. Total (With Multiplier) effects for increasing water availability (days per week) to one day for all households with less or no access. [11]

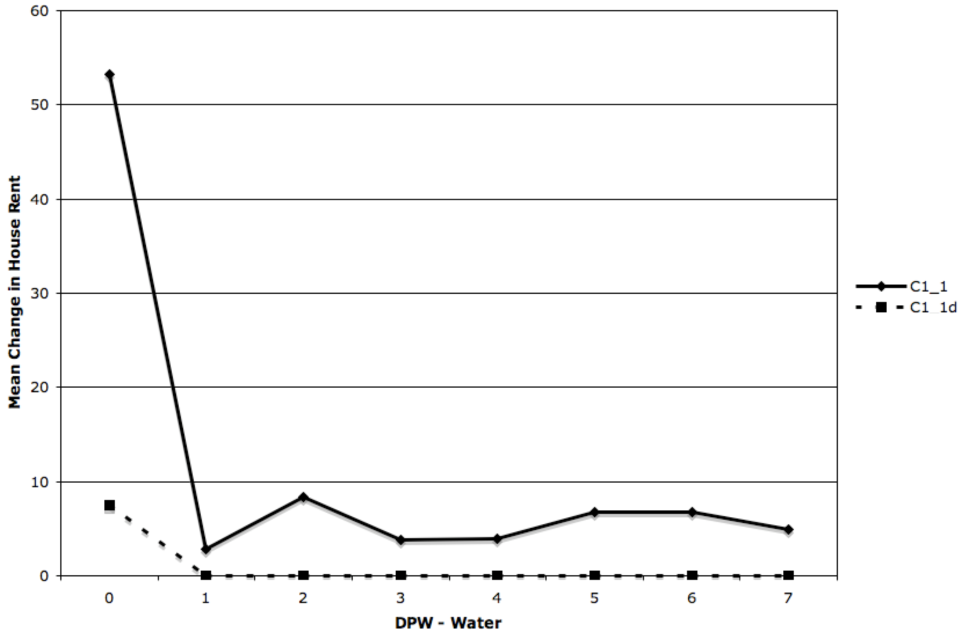
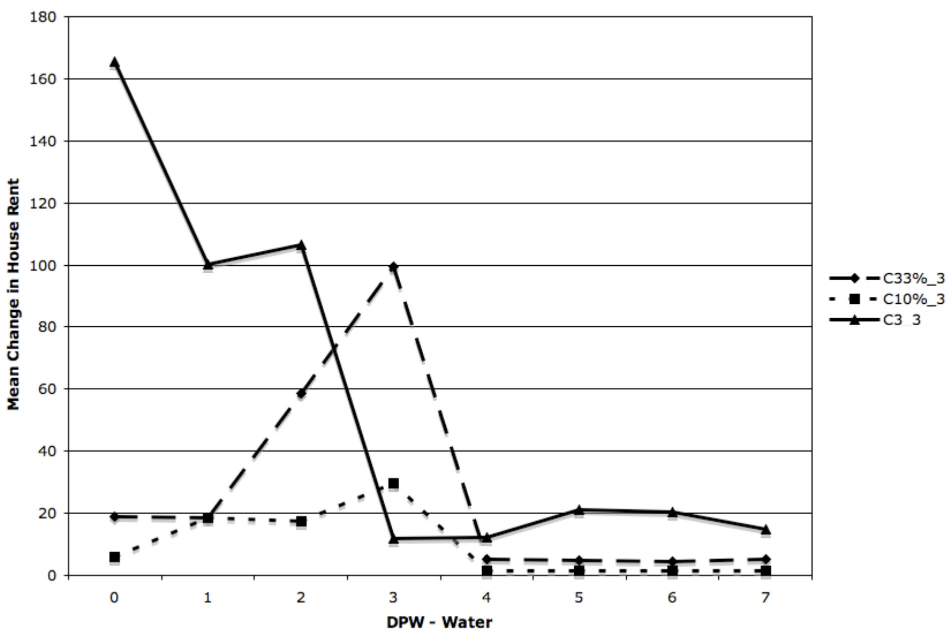


Figure 3: Bangalore: Direct effects from three alternative policy changes (see text).



We also consider the average changes for different levels of water accessibility. Figure 1 shows the average change in house prices by levels of water availability for a non-uniform change. This

[11] C1_1 shows for the total effect while the dotted line labeled C1_1d shows the direct effect that ignores the multiplier from the spatial model.

figure pertains to the simulation exercise where water availability is increased by 10% only for those households that currently have less than the mean water availability (3 DPW). Focusing only on the direct price effect, only those households with less than 3 days of water per week will face a change in their house prices (rents). More interestingly, if we also take into account the spatial spill-over effect and consider the multiplier changes in house prices as well, we observe not only that the change in house prices is much larger for all households below the mean water availability but also that all households (even those whose water access levels did not change) experience changes in their house values. Figure 2 shows similar results when comparing direct and total (with multiplier) effects of increasing to one DPW the availability of all households that currently have no water access through a direct connection in Bangalore. Figure 3 summarizes the changes in prices resulting from the three scenarios in water access change. It is interesting to note that in all cases we see that all households experience increased house values. The use of a spatial lag model allows us to observe the spill-over effects on house prices of a localized change in water availability that would otherwise be ignored in a traditional non-spatial specification.

For Bhopal the picture is very similar. Direct changes pertain only to the houses directly affected by the policy scenarios and therefore underestimate the effect on house prices over the entire city, as shown in Figures 4 and 5. Figure 6 shows the average changes for the three simulations for different levels of accessibility. For the city of Bhopal, it is interesting to see that for a non-uniform increase, households with higher levels of availability that are not directly facing the changes in water also experience higher house prices. Interestingly, the spillover effects seem to be higher for a policy that guarantees that everyone has at least one day a week of water. This may be a result of a general improvement of the conditions in the city by guaranteeing access.

Figure 4: Bhopal: Direct vs. Total (With Multiplier) effects for an Increase of 10% in water availability (days per week) for all households with less than 3 days per week. [12]

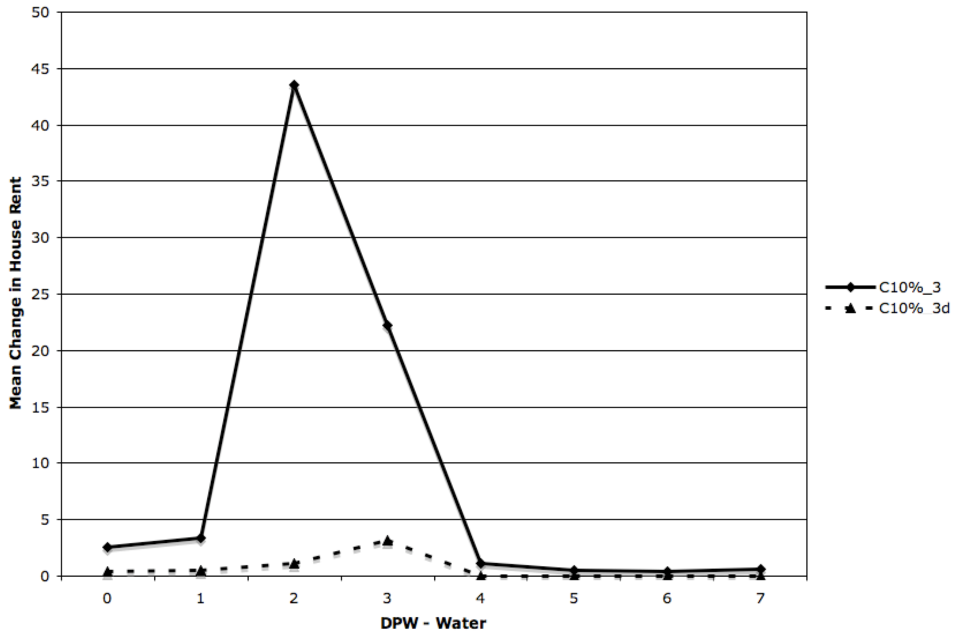
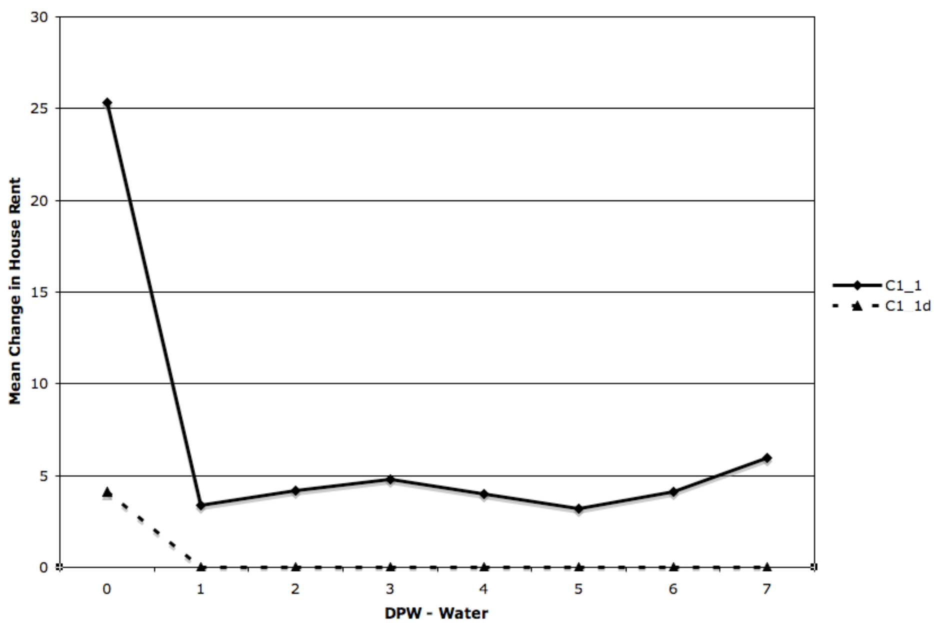


Figure 5: Bhopal: Direct vs. Total (With Multiplier) effects for increasing water availability (days per week) to one day for all households with no access. [13]



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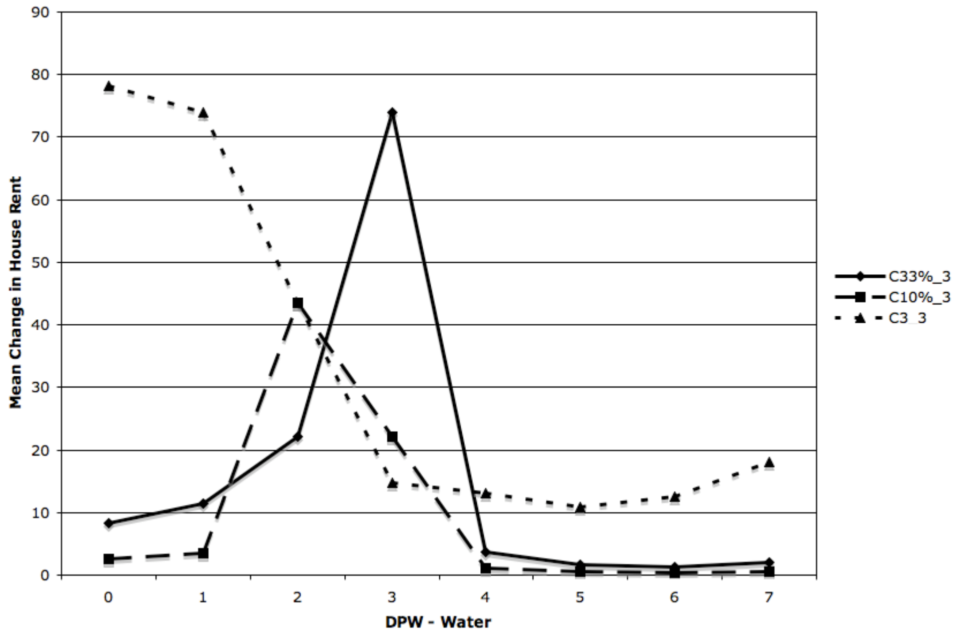
[12] C10%_3 shows the total (with multiplier) effect while the dotted line labeled C10%_3d shows the direct effect that ignores the multiplier from the spatial model.

[13] C1_1 shows the total effect while the dotted line labeled C1_1d shows the direct effect that ignores the multiplier from the spatial model.

Figure 6: Bhopal: Direct Effects from three alternative policy changes. 33% and 10% increases for households with less than 3 days per week and bringing availability to at least 3 days per week.



Finally, we consider the spatial distribution of the impacts by computing an estimate for the average change by ward. This is obtained by taking the average change in value for all the houses in the sample that are located in a given ward. This allows for an assessment of the spatial distribution of the impact of the policy change. Figures 7 through 10 summarize this for the cities of Bhopal and Bangalore. The spatial distribution of the average changes is very different from one policy to the other in both cities.

To illustrate this point, we illustrate the case of Bangalore. For a 10% increase in water access for those households below the mean level, in Bangalore the highest average changes (dark red) are observed for the ward of Kodandaramapura in the North and Hanumanthanagara in the South-West of the city. For the policy to increase the availability to one day per week for the same households, the highest change in average house rents (dark red) are observed in five Eastern wards: Kaval Bairasandra, Banasavadi, Benniganahalli, Lingarajapura and Sir C.V. Ramannagara.

Figure 7: Bangalore: Average Change in Water Availability by Ward (10% Increase for all households with less than 3 DPW)

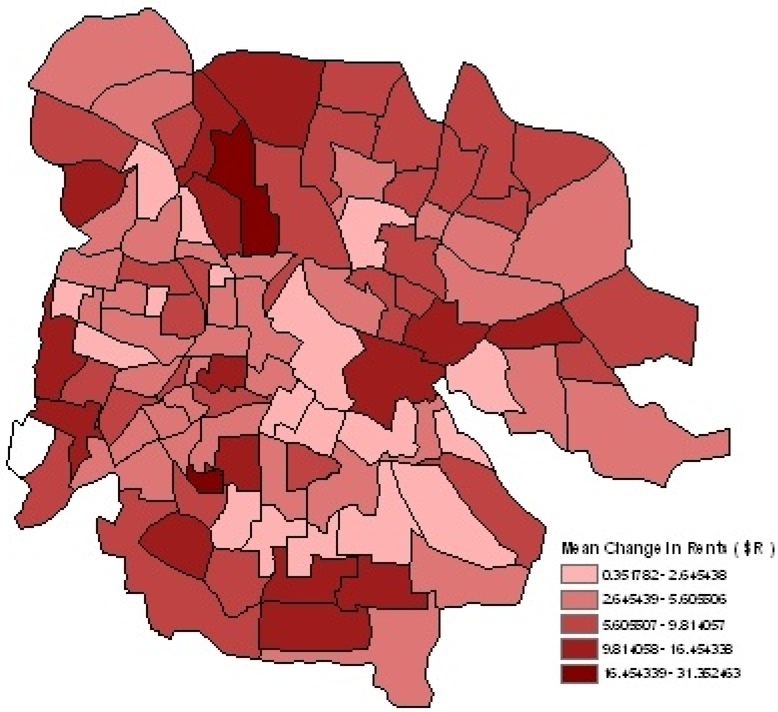


Figure 8: Bangalore: Average Change in Water Availability by Ward (all households with less 1 DPW are guaranteed 1DPW)

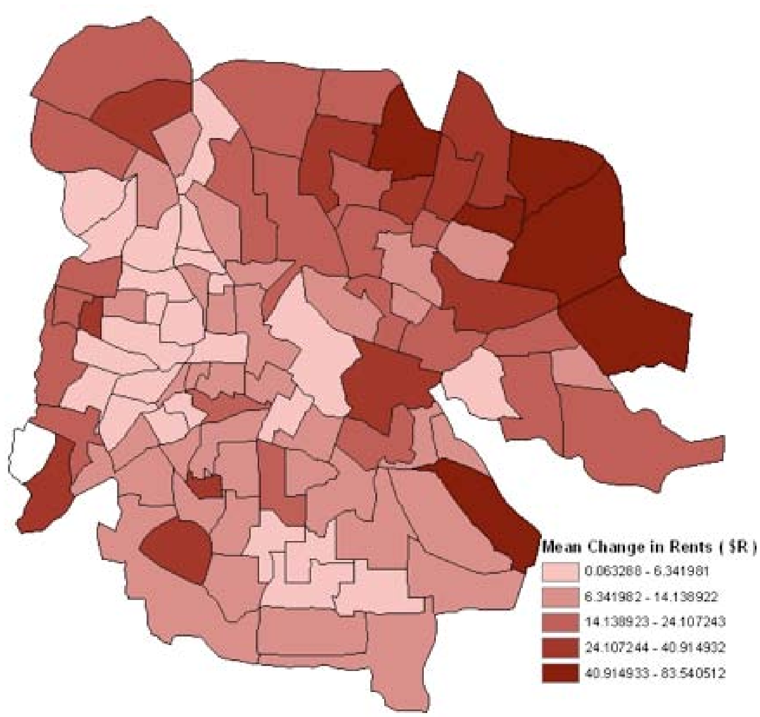


Figure 9: Bhopal: Average Change in Water Availability by Ward (10% Increase for all households with less than 3 DPW)

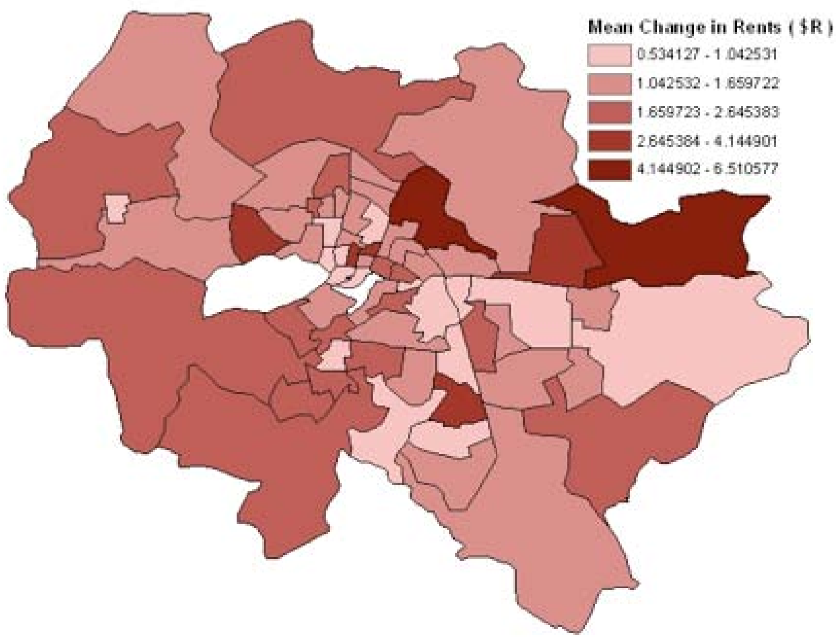
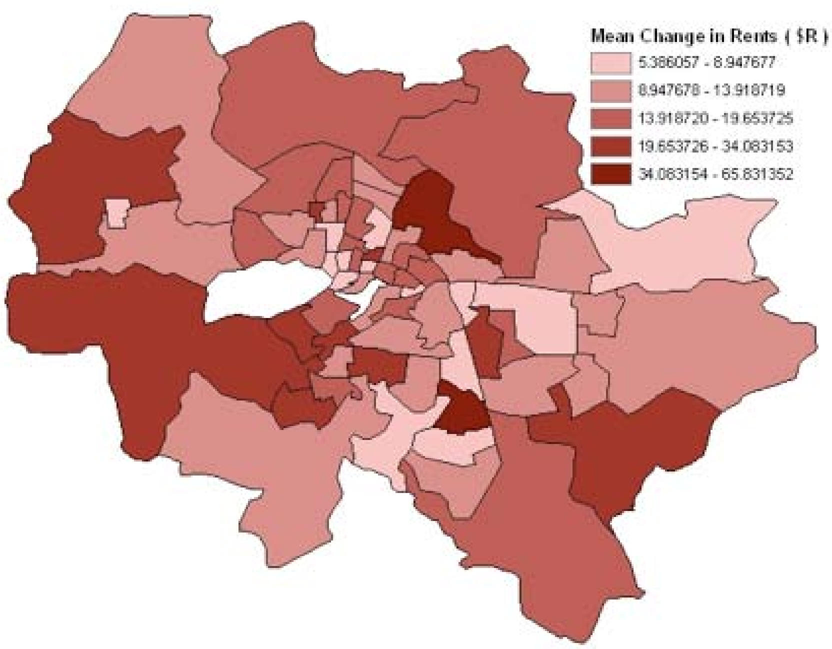


Figure 10: Bhopal: Average Change in Water Availability by Ward (all households with less 1 DPW are guaranteed 1DPW)



VIII. Conclusions

This paper presents a spatially explicit approach to estimating willingness to pay for water supply in two Indian cities. By incorporating neighborhood effects in spatial hedonic estimates of the capitalization of improved water supply, we show that total benefits that include direct effects and neighborhood multipliers are considerably higher than estimates from non-spatial estimation. For Bangalore and Bhopal, the spatial estimates exceed standard MWTP estimates by 23 percent and 16 percent, respectively. Although we cannot isolate the specific underlying process by which neighbors' quality of access affects each other, there are a number of possibilities. Generally, real estate markets tend to factor in neighborhood quality, so upgrading of a dwelling unit or maintenance of yards on a block has an effect on the value of all houses on the block. High quality water supply and sanitation also has considerable health benefits. One could thus interpret these neighborhood effects as specific health externalities as neighbors' improved living conditions reduce the risk of communicable diseases. Beyond these more speculative conclusions, the policy implications of these results are clear. By looking at individual or private benefits only, we may underestimate the overall social welfare from investing in service supply especially among the poorest residents in developing country cities. In decision making under strict efficiency rules, this may lead to an underinvestment in critical infrastructure.

Besides presenting estimates of MWTP, we also report on a number of policy simulations that show how benefit estimates can be derived for each household on the basis of its actual (rather than mean) characteristics. The resulting information can be mapped geographically which informs prioritization and sequencing of investment decisions. This approach results in a flexible framework in which urban investment options can be evaluated. Using efficiency criteria, investments could be prioritized in areas where returns in the form of housing value increases (and thus user fee or tax increases) are highest. Introducing equity concerns would possibly alter the investment schedule to first target the poorest households where returns may be lower, but welfare benefits and positive health spillovers may be highest.

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APPENDIX

Table AA 1: Estimates hedonic price (rent) equation, Bhopal

		BHOPAL	
VARIABLES		OLS	LAG
WATER DPW		0.0257	0.0242
	Classic	(0.0083) *	(0.0082) *
	White	(0.0083) *	(0.0082) *
	HAC-ep	(0.0092) *	(0.0089) *
W_RENT		----	0.2421
	Classic	----	(0.0390) *
	White	----	(0.0366) *
	HAC-ep	----	(0.0380) *
SIZE		0.0002	0.0002
	Classic	(0.0000) *	(0.0000) *
	White	(0.0000) *	(0.0000) *
	HAC-ep	(0.0000) *	(0.0000) *
ROOMS		0.0529	0.0542
	Classic	(0.0069) *	(0.0068) *
	White	(0.0088) *	(0.0088) *
	HAC-ep	(0.0090) *	(0.0088) *
BATHROOMS		0.2786	0.2637
	Classic	(0.0301) *	(0.0299) *
	White	(0.0336) *	(0.0329) *
	HAC-ep	(0.0354) *	(0.0336) *
FLOOR		0.2488	0.2339
	Classic	(0.0538) *	(0.0533) *
	White	(0.0451) *	(0.0445) *
	HAC-ep	(0.0480) *	(0.0461) *
WALLS		0.1377	0.1197
	Classic	(0.0507) *	(0.0503) **
	White	(0.0455) *	(0.0446) **
	HAC-ep	(0.0486) *	(0.0478) **
ROOF		0.4517	0.4145
	Classic	(0.0415) *	(0.0415) *
	White	(0.0425) *	(0.0423) *
	HAC-ep	(0.0455) *	(0.0439) *
KITCHEN		0.1366	0.1656
	Classic	(0.1523)	(0.1509)
	White	(0.1272)	(0.1199)
	HAC-ep	(0.1288)	(0.1201)
WOMEN SAFE		-0.0049	-0.0164

	Classic	(0.0449) *	(0.0445)
	White	(0.0415) *	(0.0418)
	HAC-ep	(0.0465) *	(0.0461)
ELECTRICITY		0.1772	0.1649
	Classic	(0.0433) *	(0.0429) *
	White	(0.0415) *	(0.0408) *
	HAC-ep	(0.0446) *	(0.0425) *
NO DUMP		0.0366	0.0282
	Classic	(0.0339) *	(0.0336)
	White	(0.0330) *	(0.0330)
	HAC-ep	(0.0322) *	(0.0318)
TOILET-SEWER		0.1417	0.0963
	Classic	(0.0472) *	(0.0473) **
	White	(0.0459) *	(0.0462) **
	HAC-ep	(0.0555) **	(0.0534)
ELSE		0.0574	0.0295
	Classic	(0.0866)	(0.0859)
	White	(0.0946)	(0.0941)
	HAC-ep	(0.0926)	(0.0918)
HAND PUMP		0.1034	0.0662
	Classic	(0.1283)	(0.1272)
	White	(0.1191)	(0.1221)
	HAC-ep	(0.1233)	(0.1284)
TUBE WELL		0.1764	0.1801
	Classic	(0.0688) **	(0.0681)
	White	(0.0694) **	(0.0693) **
	HAC-ep	(0.0719) **	(0.0721) **
COMMON TUBE WELL		0.0117	-0.0034
	Classic	(0.0733)	(0.0726)
	White	(0.0724)	(0.0722)
	HAC-ep	(0.0848)	(0.0832)
COMMON TAP		-0.0760	-0.0549
	Classic	(0.0536)	(0.0532)
	White	(0.0543)	(0.0539)
	HAC-ep	(0.0592)	(0.0585)
COMMON HAND PUMP		-0.1266	-0.0968
	Classic	(0.0598) **	(0.0594)
	White	(0.0565) **	(0.0562)
	HAC-ep	(0.0615) **	(0.0592)
TANKER		-0.0414	-0.0408
	Classic	(0.0988)	(0.0979)
	White	(0.1096)	(0.1074)
	HAC-ep	(0.1141)	(0.1060)
OTHER		-0.1409	-0.2070
	Classic	(0.4654)	(0.4611)

	White	(0.4054)	(0.4347)
	HAC-ep	(0.4507)	(0.4715)
RAIN		0.8814	1.1967
	Classic	(0.6558)	(0.6514)
	White	(0.1598)	(0.1649)
	HAC-ep	(0.1579)	(0.1682)
SURFACE		-0.2928	-0.4021
	Classic	(0.3315)	(0.3287)
	White	(0.1201)	(0.1649)
	HAC-ep	(0.1401)	(0.1831)
BOTTLED		-0.1118	-0.0144
	Classic	(0.3257)	(0.3229)
	White	(0.2065)	(0.2142)
	HAC-ep	(0.1998)	(0.2063)
CONSTANT		5.2237	3.6260
	Classic	(0.1917) *	(0.3199) *
	White	(0.1671) *	(0.2913) *
	HAC-ep	(0.1872) *	(0.2927) *
R-squared (var ratio)		0.6438	0.6517
		STATISTIC	p-value
LM-Err		6.818	0.009
LM-Lag		31.56	0.000
Robust LM-Err		4.52	0.033
Robust LM-Lag		29.27	0.000
Anselin Keleijian		7.37	0.006

* Significant only at 1%　　** Significant only at 5%

Table AA2: Estimates hedonic price (rent) equation, Bangalore

		BANGALORE	
VARIABLES		OLS	LAG
WATER DPW		0.0326	0.0287
	Classic	(0.0084)*	(0.0083)*
	White	(0.0088)*	(0.0086)*
	HAC-ep	(0.0096)*	(0.0090)*
W_RENT		---	0.2429
	Classic	---	(0.0368)*
	White	---	(0.0396)*
	HAC-ep	---	(0.0439)*
SIZE		0.000	0.0001
	Classic	(0.0000)*	(0.0000)*
	White	(0.0000)*	(0.0000)*
	HAC-ep	(0.0000)*	(0.0000)*
ROOMS		0.0438	0.0444
	Classic	(0.0054)*	(0.0053)
	White	(0.0070)*	(0.0068)*
	HAC-ep	(0.0079)*	(0.0076)*
BATHROOMS		0.1782	0.1667
	Classic	(0.0180)	(0.0178)
	White	(0.0806) **	(0.0770) **
	HAC-ep	(0.0830) **	(0.0792) **
FLOOR		-0.1462	-0.1544
	Classic	(0.1166)	(0.1150)
	White	(0.1607)	(0.1544)
	HAC-ep	(0.1568)	(0.1501)
WALLS		0.3217	0.2964
	Classic	(0.0731)	(0.0722)
	White	(0.0772)	(0.0759)
	HAC-ep	(0.0846)	(0.0826)
ROOF		0.5638	0.5371
	Classic	(0.0375)	(0.0372)
	White	(0.0424)	(0.0416)
	HAC-ep	(0.0446)	(0.0421)
KITCHEN		-0.0304	0.0489
	Classic	(0.1587)	(0.1569)
	White	(0.1771)	(0.1779)
	HAC-ep	(0.1814)	(0.1825)
CRIME DECR.		-0.0359	-0.0421
	Classic	(0.0304)	(0.0300)

	White	(0.0300)	(0.0293)
	HAC-ep	(0.0332)	(0.0316)
ELECTRICITY		0.6420	0.6357
	Classic	(0.1197)*	(0.1180)*
	White	(0.1286)*	(0.1253)*
	HAC-ep	(0.1496)*	(0.1391)*
TOILET-SEWER		0.2516	0.2293
	Classic	(0.0297)*	(0.0294)*
	White	(0.0316)*	(0.0308)*
	HAC-ep	(0.0357)*	(0.0342)*
TUBE WELL		0.0784	0.0737
	Classic	(0.0403) **	(0.0397) **
	White	(0.0407) **	(0.0396) **
	HAC-ep	(0.0426) **	(0.0409) **
TANKER		0.1876	0.2120
	Classic	(0.1944)	(0.1917)
	White	(0.1126)	(0.1285)
	HAC-ep	(0.1151)	(0.1338)
OTHER		-0.1360	-0.0365
	Classic	(0.1299)	(0.1290)
	White	(0.1502)	(0.1533)
	HAC-ep	(0.2007)	(0.1867)
SURFACE		0.3951	0.4147
	Classic	(0.2398)	(0.2364)
	White	(0.1431)	(0.1342) **
	HAC-ep	(0.1416)	(0.1295)
FOUNTAIN		-0.2775	-0.2638
	Classic	(0.0448)*	(0.0442)*
	White	(0.0471)*	(0.0465)*
	HAC-ep	(0.0505)*	(0.0487)*
COMMON TUBE		-0.3279	-0.3182
	Classic	(0.0557)*	(0.0549)*
	White	(0.0664)*	(0.0661)*
	HAC-ep	(0.0757)*	(0.0740)*
CONSTANT		6.0573	4.1224
	Classic	(0.2515)*	(0.3842)*
	White	(0.2813)*	(0.4069)*
	HAC-ep	(0.2998)*	(0.4586)*
R-squared (var ratio)		0.5620	0.5687
		STATISTIC	p-value
LM-Err		37.94	0.000
LM-Lag		82.02	0.000
Robust LM-Err		2.32	0.127
Robust LM-Lag		46.40	0.000
Anselin Keleijian		3.84	0.05

* Significant only at 1%   ** Significant only at 5%